Lower Limb Posture Capture Using Quaternion Kalman Filter

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Abstract. Due to the accuracy requirements of the human body lower limb posture capture system, this paper proposes a quaternion Kalman filter-based human body lower limb posture capture method. Firstly, we employ the wearable inertial sensors to collect posture data of the lower limbs. Then, for the purpose of weakening the interference of the noise to the posture data of the sensors, the quaternion Kalman filter is designed. With the output of the quaternion Kalman filter, the lower limb joints' spatial position coordinates can be computed. The experimental results show that the proposed quaternion Kalman filter-based scheme can effectively reduce the attitude error, which make the attitude expression more intuitive and accurate.

Keywords: Quaternion · Kalman filter · Position calculation · Wearable inertial sensor

1 Introduction

In recent decades, due to the increasing aging of Chinese society and people's pursuit of high-quality life, patients with sports impairment have increasingly demanded effective rehabilitation training [1]. The inertial sensor posture capture system has the advantages of low cost, convenient operation and simple system composition, which is conducive to the use of civilians in rehabilitation training [4]. The advancement of wearable sensor technology provides an important breakthrough for clinicians and graduate schools engaged in rehabilitation medicine [3]. It integrates gyroscopes, accelerometers, and magnetometers. The accuracy will be interfered by drift errors, motion acceleration, and surrounding environmental magnetic fields, resulting in inaccurate attitude data output. How to ensure the accuracy of posture information has become a hot topic [8].

Kalman filter is a magic filter algorithm, it is a state estimation algorithm that combines prior experience and measurement update. Kalman filtering can be applied to any dynamic system with uncertain information to make basic

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predictions for the next direction of the system. Once accompanied by various disturbances, the Kalman transform can always point out what actually happened. Recently, Kalman filtering has been implemented in many different waves [7].

The accuracy of using wearable sensors to obtain posture data may be affected by the environment, the joints tracked, and the type of exercise performed, resulting in insufficient accuracy. This article presents an algorithm for capturing the pose of the human body's lower limbs based on the quaternion Kalman filter. This method uses wearable inertial sensors to capture the posture data of the lower limbs, uses a quaternion Kalman filter as a local data fusion filter, and then uses the filtered posture quaternion to calculate the three-dimensional space position of the lower limb joints. After a lot of experimental verification, it can be determined that this scheme makes the acquired posture more accurate and intuitive.

The framework of this article is as follows: Sect. 2 designs the posture capture scheme of human lower limbs. Section 3 discusses the quaternion Kalman filter and the solution of lower limb joint positions. Section 4 verifies the quaternion Kalman filter through the results of semi-physical simulation. Section 5 summarizes this article.

2 Data Fusion Model

In this section, we will design the data fusion model used in this work. Since the quaternion has the advantages of no gimbal deadlock phenomenon, high efficiency, and convenient to use, we choose the quaternion as the attitude data of the inertial sensor. In order to collect posture information of the lower limbs, five wearable inertial sensors are used to place the abdomen, thigh and calf of the human body respectively, and then the posture information will be collected. The block diagram of the quaternion Kalman filter system is shown in Fig. 1. It includes 5 quaternion Kalman filter local filters, the filter outputs the posture quaternion $\mathbf{Q}$, and uses the output results to calculate the position of the lower limb joints to obtain accurate and intuitive lower limb posture.

Equation (1) represents the state equation of the filter in the fusion model, taking the attitude quaternion of each sensor as the state variable.

$$\mathbf{Q}(t)^l = \begin{bmatrix} 1 & -\frac{1}{2}\omega_x(t-1)T & -\frac{1}{2}\omega_y(t-1)T & -\frac{1}{2}\omega_z(t-1)T \\ \frac{1}{2}\omega_x(t-1)T & 1 & \frac{1}{2}\omega_z(t-1)T & -\frac{1}{2}\omega_y(t-1)T \\ \frac{1}{2}\omega_y(t-1)T & -\frac{1}{2}\omega_z(t-1)T & 1 & \frac{1}{2}\omega_x(t-1)T \\ \frac{1}{2}\omega_z(t-1)T & \frac{1}{2}\omega_y(t-1)T & -\frac{1}{2}\omega_x(t-1)T & 1 \end{bmatrix} \mathbf{Q}(t-1)^l + \mathbf{w}(t-1)^l, \tag{1}$$

where $\mathbf{Q}(\mathrm{t})^l = \begin{bmatrix} q_0 \; q_1 \; q_2 \; q_3 \end{bmatrix}^T$ represents the state vector of the filter of the l^{th} sensor at the time index t, $\mathrm{l} \in (1, n)$, n=5. T represents the sampling period; $(\omega_x(t-1), \omega_y(t-1), \omega_z(t-1))$ represents the projection of the angular velocity from the n system to the b system in the b system at the time index t, that is output value of the gyroscope. $\mathbf{w}(t-1)^l \sim \mathcal{N}\left(0, \mathbf{G}^l\right)$ is the process noise.

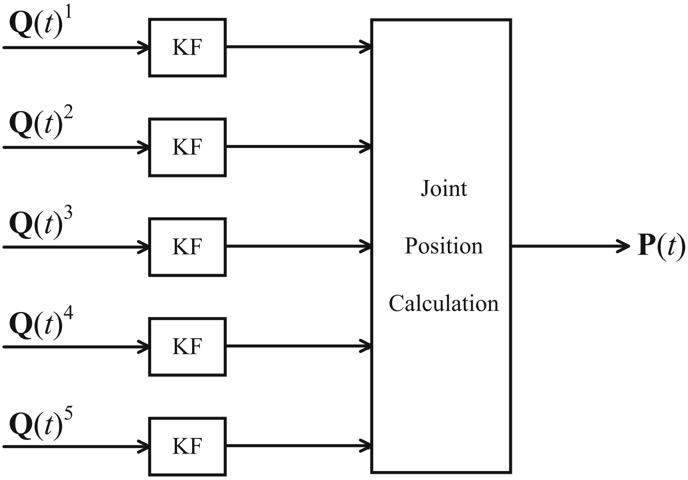

Fig. 1. Quaternion Kalman filter structure diagram.

The measurement equation used in this work can be written as:

$$\mathbf{Z}(t)^l = \mathbf{I}_{4\times 4}\mathbf{Q}(t)^l + \mathbf{\Gamma}(t)^l, \tag{2}$$

where $\mathbf{Z}(\mathrm{t})^l = \left[q_0\ q_1\ q_2\ q_3\right]^T$ represents the measured value of the l^{th} sensor. $\mathbf{I}_{4\times 4}$ represents the 4th order identity matrix. $\mathbf{\Gamma}(t)^l \sim \mathcal{N}\left(0, \mathbf{R}^l\right)$ is the measurement noise.

3 Quaternion Kalman Filter and Calculation of Lower Limb Joint Position

This section will design the quaternion Kalman filter based on model (1) and (2) as the filter of each sensor. First, we rewrite the model (1) (2) as follows:

$$\begin{cases} \mathbf{Q}(t)^l = \mathbf{F}(t-1)^l\mathbf{Q}(t-1)^l + \mathbf{w}(t-1)^l \\ \mathbf{Z}(t)^l = \mathbf{H}(t)^l\mathbf{Q}(t)^l + \mathbf{\Gamma}(t)^l \end{cases}, \tag{3}$$

In this model, the system parameter

$$\mathbf{F}(\mathrm{t}-1) = \begin{bmatrix} 1 & -\frac{1}{2}\omega_x(t-1)T & -\frac{1}{2}\omega_y(t-1)T & -\frac{1}{2}\omega_z(t-1)T \\ \frac{1}{2}\omega_x(t-1)T & 1 & \frac{1}{2}\omega_z(t-1)T & -\frac{1}{2}\omega_y(t-1)T \\ \frac{1}{2}\omega_y(t-1)T & -\frac{1}{2}\omega_z(t-1)T & 1 & \frac{1}{2}\omega_x(t-1)T \\ \frac{1}{2}\omega_z(t-1)T & \frac{1}{2}\omega_y(t-1)T & -\frac{1}{2}\omega_x(t-1)T & 1 \end{bmatrix}$$

is used as the state transition matrix, and the attitude quaternion of the sensor is used as the State vector [5]. Choose attitude quaternion as the observation vector. Because the state quantity and observation vector are both attitude quaternion, so the observation matrix is a 4th order identity matrix. $\mathbf{H}(t)^l = \mathbf{I}_{4\times4}$. According to model (3), quaternion Kalman filter can be designed.

First, it is known that the attitude quaternion output by the sensor is used as the initial value $\mathbf{Q}(0)^l$ of the state estimator. Then, $\mathbf{Q}(t|t-1)^l$ can be estimated a priori on the time index t using Eq. (4) and Eq. (5).

$$\mathbf{Q}(t|t-1)^l = \mathbf{F}(t-1)^l\mathbf{Q}(t-1)^l, \tag{4}$$

$$\mathbf{P_Q}(t|t-1)^l = \mathbf{F}(t-1)^l\mathbf{P_Q}(t-1)^l\left(\mathbf{F}(t-1)^l\right)^T + \mathbf{G}^l, \tag{5}$$

where $\mathbf{Q}(t|t-1)^l$ represents the prior estimation of the state quantity at the time index of t, and $\mathbf{P_Q}(t|t-1)^l$ represents the predicted value of the covariance of the prior estimation error of the state quantity. $\mathbf{G}^l$ represents the process noise variance of the l^{th} sensor. Then, Eqs. (6), (7) and (8)can be used to update the state quantity $\mathbf{Q}(t)^l$ on the time index t.

$$\mathbf{K}(t)^l = \mathbf{P_Q}(t|t-1)^l\left(\mathbf{H}(t)^l\right)^T\left[\mathbf{R}^l + \mathbf{H}(t)^l\mathbf{P_Q}(t|t-1)^l\left(\mathbf{H}(t)^l\right)^T\right]^{-1} \tag{6}$$

$$\mathbf{Q}(t)^l = \mathbf{Q}(t|t-1)^l + \mathbf{K}(t)^l\left[\mathbf{Z}(t)^l - \mathbf{H}(t)^l\mathbf{Q}(t|t-1)^l\right] \tag{7}$$

$$\mathbf{P_Q}(t)^l = \left[\mathbf{I} - \mathbf{K}(t)^l\mathbf{H}(t)^l\right]\mathbf{P_Q}(t|t-1)^l \tag{8}$$

where $\mathbf{K}(t)^l$ is expressed as the Kalman gain coefficient, which can fuse the measured value and the state quantity estimated a priori, and the result of the measured quantity and the state quantity estimated a priori can be weighed according to the magnitude of $\mathbf{K}(t)^l$. $\mathbf{R}^l$ represents the measurement noise variance of the l^{th} sensor. $\mathbf{Q}(t)^l$ represents the posterior estimation of the state quantity at the time index t. $\mathbf{P_Q}(t)^l$ represents the updated value of the error covariance of the state quantity.

The filter outputs the attitude quaternion, which is expressed as the rotation from the navigation coordinate system to the carrier coordinate system, so the rotation matrix $\mathbf{C}_\mathrm{n}^\mathrm{b}$ can be expressed as:

$$\mathbf{C}_\mathrm{n}^\mathrm{b} = \begin{bmatrix} 2q_0^2+2q_1^2-1 & 2q_1q_2+2q_0q_3 & 2q_1q_3-2q_0q_2 \\ 2q_1q_2-2q_0q_3 & 2q_0^2+2q_2^2-1 & 2q_2q_3+2q_0q_1 \\ 2q_1q_3+2q_0q_2 & 2q_2q_3-2q_0q_1 & 2q_0^2+2q_3^2-1 \end{bmatrix}, \tag{9}$$

The coordinates of the knee joint and ankle joint are calculated based on the posture quaternion and limb size output by the quaternion Kalman filter and the position of the reference point. The detailed calculation method will be introduced below.

First, determine the reference system as the C system. This method uses the coordinate system of the sensor Xsens Dot where the abdomen is located as the reference coordinate system, that is, the C coordinate system. The joint coordinates calculated are all the position coordinates in this reference system.

Take the right leg joint as an example. This method requires that the direction of the right hip joint coordinate system is consistent with the direction of the reference coordinate system, and the coordinate system of the lower limb joints is required to be consistent with the coordinate system of the Xsens Dot sensor installed on the thigh and calf. Lp is the thigh length; Ld is the calf length. The direction of the sensor's own coordinate system is shown in Fig. 2, which conforms to the right-handed coordinate system [6]. The installation position of the sensor and the direction of the sensor and joint position coordinate system are shown in Fig. 3 [2].

Fig. 2. Sensor coordinate system.

Then the rotation matrix from the direction of the right knee joint coordinate system (k system) to the direction of the reference coordinate system (C system) can be expressed as:

$$\mathbf{C}_{\mathrm{k}}^{\mathrm{C}} = \mathbf{C}_{\mathrm{n}}^{\mathrm{C}}\mathbf{C}_{\mathrm{k}}^{\mathrm{n}} = \mathbf{C}_{\mathrm{n}}^{\mathrm{C}}(\mathbf{C}_{\mathrm{n}}^{\mathrm{k}})^{\mathrm{T}}, \tag{10}$$

The rotation matrix from the direction of the right ankle joint coordinate system (a system) to the direction of the reference coordinate system (C system) can be expressed as:

$$\mathbf{C}_{\mathrm{a}}^{\mathrm{C}} = \mathbf{C}_{\mathrm{n}}^{\mathrm{C}}\mathbf{C}_{\mathrm{a}}^{\mathrm{n}} = \mathbf{C}_{\mathrm{n}}^{\mathrm{C}}(\mathbf{C}_{\mathrm{n}}^{\mathrm{a}})^{\mathrm{T}}, \tag{11}$$

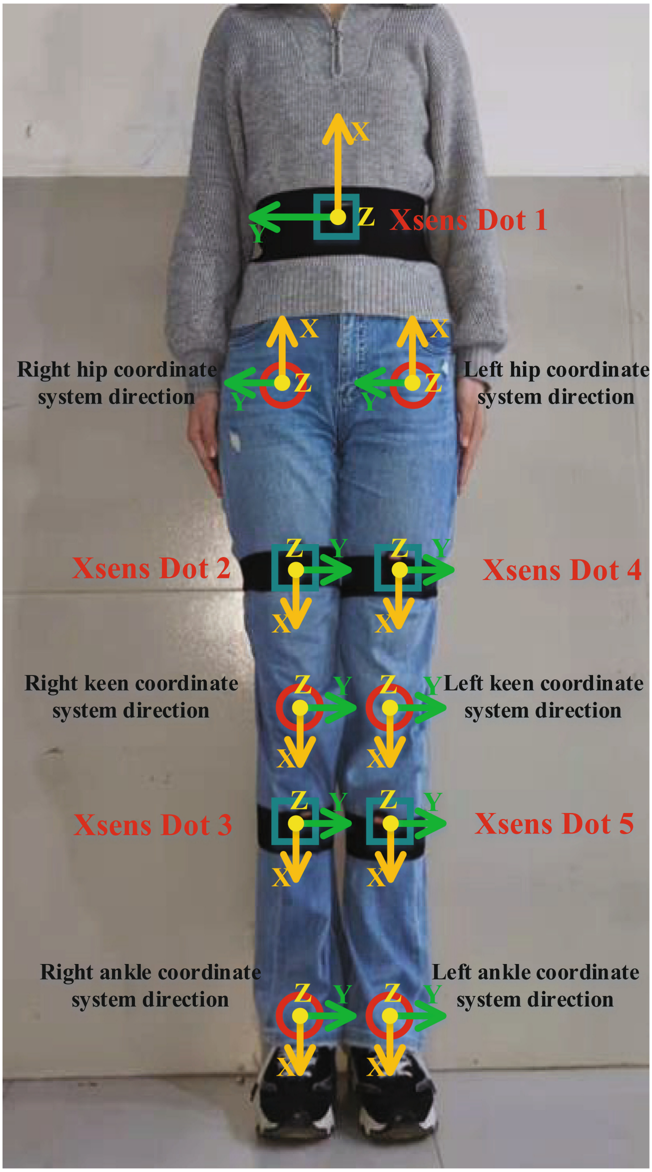

Fig. 3. The installation position of the sensor and the direction of the sensor and joint position coordinate system.

In the reference coordinate system (C coordinate system), through actual measurement, the three-dimensional space coordinates of the right hip joint position can be obtained:

$$\mathbf{P_h} = (\mathrm{x_h}, \mathrm{y_h}, \mathrm{z_h}), \tag{12}$$

Since the X-axis direction of the knee joint position coordinate system coincides with the direction of the thigh, the right knee joint only has a component in the X-axis direction relative to the right hip joint point $\mathbf{P_h}$ [4]. Then in the reference coordinate system (C), the three-dimensional space coordinates of the right knee joint can be expressed as:

$$\mathbf{P_k} = \mathrm{Lp}\mathbf{C}^{\mathrm{C}}_{\mathrm{k},1} + \mathbf{P_h}, \tag{13}$$

where $\mathbf{C}^{\mathrm{C}}_{k,1}$ is the first column vector of the rotation matrix $\mathbf{C}^{\mathrm{C}}_{k}$.

In the same way, in the reference coordinate system (C), the three-dimensional space coordinates of the right ankle joint can be expressed as:

$$\mathbf{P_a} = \mathrm{Ld}\mathbf{C}^{\mathrm{C}}_{\mathrm{a},1} + \mathbf{P_k}. \tag{14}$$

where $\mathbf{C}^{\mathrm{C}}_{\mathrm{a},1}$ is the first column vector of the rotation matrix $\mathbf{C}^{\mathrm{C}}_{\mathrm{a}}$.

The above are all steps to calculate the joint coordinates of the right leg, and the calculation method of the joint of the left leg is the same as above.

4 Experimental Test

4.1 Experimental Environment

Five wearable inertial sensors Xsens Dot were used in the experiment. The author placed the wearable inertial sensors at the reference point and the thigh and calf of the lower limbs, and tried to ensure that the sensors on the upper and lower legs were kept in the same straight line, and as far as possible to ensure that the sensor Xsens Dot at the reference point remained stationary. In the course of the experiment, with the assistance of a rehabilitation bicycle, the author simulates a patient with sports impairment to perform rehabilitation exercises for the lower limbs. The measured data environment and target personnel are shown in Fig. 4 and Fig. 5.

4.2 Performance Analysis of the Proposed Algorithm

For the convenience of observation, We compare the filtered pose quaternion-solved joint position results and the directly measured pose quaternion-solved joint position results with reference values.

Figure 6 and Fig. 7 are the distribution diagrams of the absolute error of the joint three-dimensional space position calculated by using the quaternion before and after filtering. The black point set represents the distribution of the absolute error of the joint three-dimensional space position calculated by the measured

Fig. 4. Experimental equipment and target personnel.

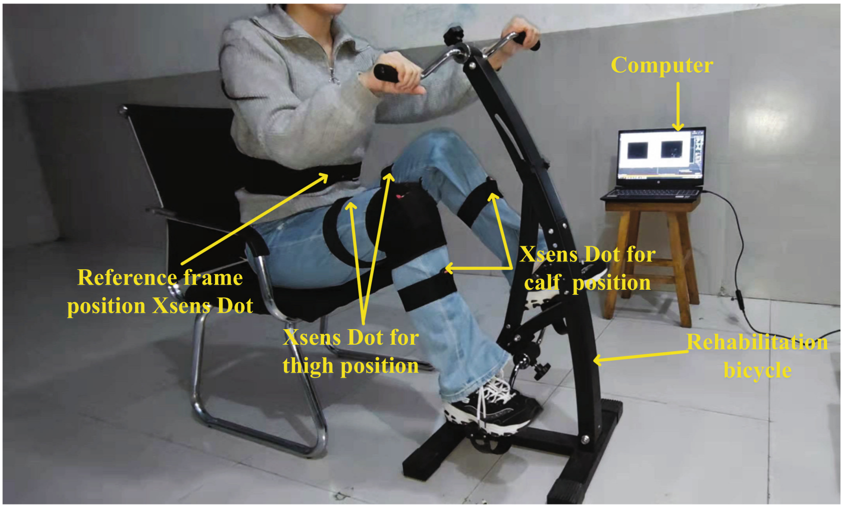

Fig. 5. Test environment.

value. The green point set represents the distribution of the absolute error of the joint three-dimensional space position calculated after filtering. It can be clearly seen that through filtering, the absolute error values of the X-axis, Y-axis, and Z-axis of the knee and ankle are significantly reduced. Therefore, it can be shown that the algorithm proposed in this paper has a good performance in reducing the absolute error.

Figure 8 and Fig. 9 are cumulative distribution function (CDF) plots of joint position errors before and after using the quaternion Kalman filtering method. As shown in the figure, the solid black line represents the CDF curve of the joint three-dimensional space position solved by the measured value. The green solid line represents the CDF curve of the joint three-dimensional space position calculated after filtering. It can be clearly seen from the figure that when y=0.9, the x value corresponding to the green solid line is smaller than the x value corresponding to the black solid line. That is to say, when the probability reaches 90 %, the joint position errors calculated by the filter value are significantly smaller than the joint position errors calculated by the measured value.

Table 1 shows the Root Mean Square Error (RMSE) before and after using the quaternion Kalman filter. It can be proved that the quaternion Kalman filter used in this experiment can effectively reduce the error of measuring joint position.

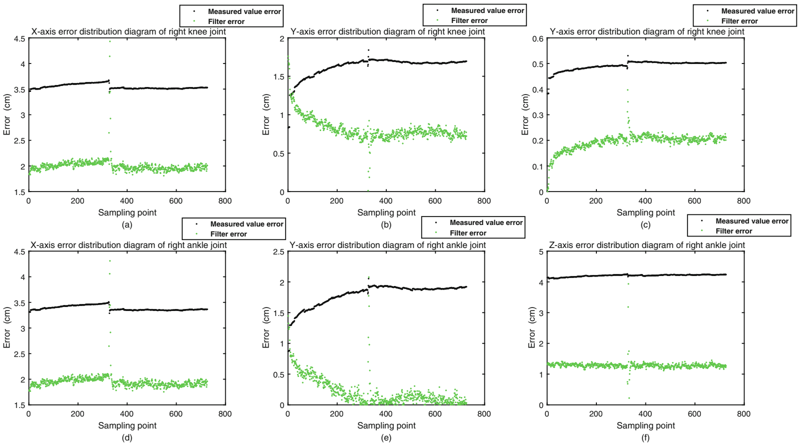

Fig. 6. Three dimensional position error distribution of right leg joint.

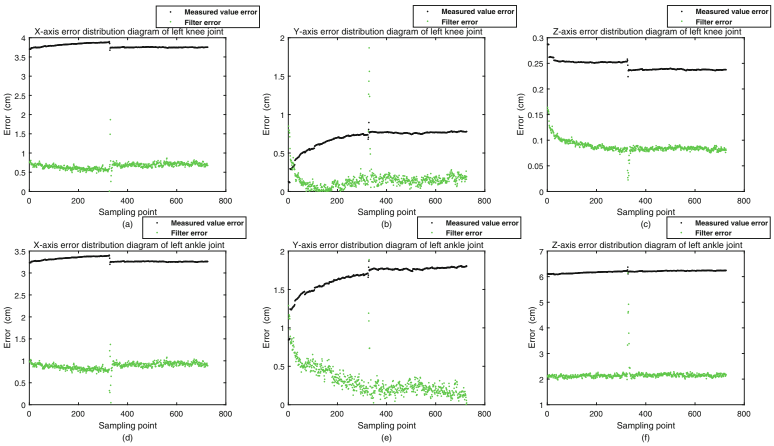

Fig. 7. Three dimensional position error distribution of left leg joint.

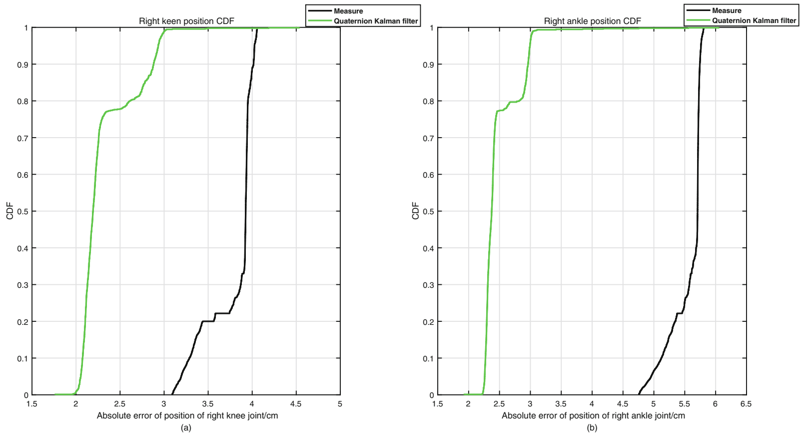

Fig. 8. CDF map of the three-dimensional space position of the right leg joint before and after filtering.

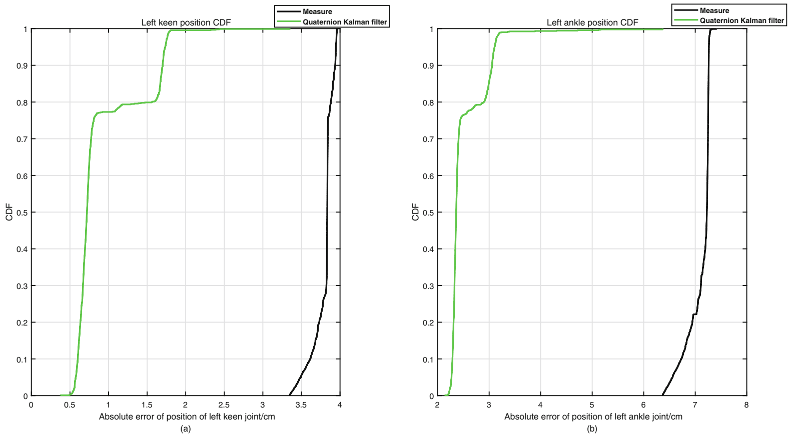

Fig. 9. CDF map of the three-dimensional space position of the left leg joint before and after filtering.

Table 1. Three-dimensional space position RMSE of joints before and after filtering.

Position	Aixs	Before filtering RMSE/cm	After filtering RMSE/cm
Right knee	X	3.4887	1.9565
	Y	1.4524	1.2612
	Z	0.45817	0.18342
Right ankle	X	3.3338	1.9025
	Y	1.5993	0.97097
	Z	4.1668	1.3026
Left knee	X	3.7244	0.7424
	Y	0.71415	0.6598
	Z	0.2622	0.12884
Left ankle	X	3.2437	0.95625
	Y	1.4911	0.90548
	Z	6.1471	2.1697

5 Conclusion

In this paper, quaternion Kalman filter is used to capture the lower limb posture. Firstly, using quaternion to express attitude can avoid the phenomenon of cardan deadlock, and the measurement noise can be reduced by filtering quaternion. Secondly, quaternion and limb length can be used to accurately calculate the three-dimensional position of the joint, so that the expression of human lower limb posture is more intuitive and easy to understand.

This method uses quaternion Kalman filters to filter the posture data output by the five sensors, and then the posture quaternion obtained before and after filtering was used to solve the three-dimensional space coordinate of the lower limb joint. Finally, the three dimensional position of the joint is compared with the reference value.

Through a large number of experiments in this article, it can be proved that through the quaternion Kalman filter and joint position calculation, more intuitive and accurate posture joint position results can be obtained.

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